Influence of Participation Rates and Service Level Differentiation on Community Driven Predictions

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Abstract. Anticipatory Vehicle Routing based on Intention Propagation (AVRIP) can help reduce drivers travel times and avoid forming congestion. The route guidance system uses information shared by participating drivers to predict future link traversal times, the time it will take a vehicle to traverse a road at a certain time in the future. Both participating and non-participating drivers benefit from these link travel time predictions. Participating drivers will receive the predictions and will adapt their route to avoid any congestion. Non-participating drivers experience less congestion because of these diversions.

The percentage of drivers participating in the AVRIP guidance is an important factor. This participation rate influences the efficiency of the system in two ways: it affects the accuracy of the predictions and it changes the number of drivers influenced by the predictions.

This paper provides a first study on the influence of the participation rate on the efficiency of AVRIP by varying the participation rate while keeping all other parameters constant in a simulated traffic network.

1 Introduction

Anticipatory Vehicle Routing using Intention Propagation (AVRIP) is a multi-agent system based Advanced Traveller Information System (ATIS). ATIS systems aim to present users with information to assist them in their route choosing process.

The AVRIP system relies on a community of participating drivers willing to share their intention with the AVRIP system. A driver's intention is the route he or she intends to follow. By combining the intentions of all participating drivers, the AVRIP system can estimate the number of vehicles on a road at a future point in time. This information is combined with historical observations to make predictions about the link travel time of the roads. These link travel time predictions, the times it takes a vehicle to traverse a road at a future point in time, are presented back to the driver. The predictions can be used to calculate the fastest route, taking into account future congestion levels.

The benefits of AVRIP as an ATIS have been described earlier [1]. This paper studies on the community driven part of AVRIP and more specifically the relative size of the community of participating drivers. A decentralized ATIS relying on

Y. Demazeau et al. (Eds.): PAAMS 2014, LNAI 8473, pp. 62–73, 2014.

driver participation cannot realistically be deployed at once. The system will undergo an adoption process resulting in varying participation rates. Analyzing the effects of the varying participation rate is necessary as the percentage of drivers participating in the system can influence the accuracy of the system. The study will provide useful information on the effectiveness and challenges throughout this adoption process.

A first consequence of the participation rate is its influence on the prediction process. An insufficient number of participating drivers makes it impossible to accurately predict link travel times. Participating drivers would receive incorrect information leading to inappropriate routing decisions. One research questions looked at in this paper is the minimal populations size required for AVRIP to function.

A second consequence of the participation rate is the influence of participating drivers on the traffic. This effect has been observed by Wunderlich et al. [2]. When facing a congested traffic network, participating vehicles using an advanced traffic information system will start diverting to alternative routes. A small community of participating vehicles would find little traffic on the alternative routes. A large community of participating vehicles could cause congestion on the alternative routes. The situation is reversed for the non-participating drivers. When facing a partly congested network, the congestion will dissolve if enough participating vehicles reroute. The benefit for the non-participating drivers increases when the size of the participating community increases. The benefit for the participating drivers decreases when their community size increases. Whether the findings of Wunderlich et al. hold for AVRIP is the second research question addressed in this paper.

This paper is organized as follows. First a brief overview of the Anticipatory Vehicle Routing using Intention Propagation is given (Section 2). The description is limited to the essentials, further details about AVRIP can be found starting from [1]. Section 3 discusses research related to this paper and in particular the work and experiments by Wunderlich and Kaufman. In Section 4 the experiment setup is described. The results of the simulations are analyzed in Section 5, before drawing conclusions in Section 6.

2 Anticipatory Vehicle Routing Using Intention Propagation

In [1] we propose a decentralized advanced traffic information system based on a multi-agent architecture and Ant Colony Optimization [3]. In this system, vehicle agents represent the interests of the drivers and communicate with infrastructure agents representing the road infrastructure elements such as roads and crossroads. By propagating their intentions, the route the driver intends to follow, the vehicle agents inform the infrastructure agents of their pending arrival. The infrastructure agents in return, use this information to forecast future link traversal times and share these forecasts with the vehicle agents. The forecast information allows the vehicle agents to make better, more informed, decisions.

The system is decentralized, it does not rely on a central component. Vehicle agents are assumed to be deployed in the vehicle they represent. Infrastructure agents are assumed to be deployed near the real-world infrastructure element they represent. This last assumption is not a requirement, the only requirement is that the infrastructure agent has sufficient real-time information about the real-world element it represents and can communicate with vehicle agents.

The intention propagation is initiated by the vehicle agents. At regular intervals, the vehicle agents dispatch mobile agents to inform infrastructure agents of the vehicles' intentions. By traversing the same path as the vehicle plans to take, the mobile agents can interact with all relevant infrastructure agents. Every interaction has two consequences. First, the infrastructure element receives information about a pending visit. Second, the information provided by the infrastructure agent allows the mobile agent to estimate its arrival time at the next infrastructure element. This exchange of information allows the mobile agent to inform subsequent infrastructure agents of its estimated arrival time.

Upon arrival at the vehicles destination, the mobile intention agent will have informed all agents on its path and will have an estimated arrival time for the vehicles destination. This estimated arrival time is communicated back to the vehicle agent and allows it to monitor its estimated arrival time.

The information stored in the infrastructure agent has an expiration time, somewhat similar to how pheromones operate in nature. If the information is not refreshed, it will evaporate. As long as the vehicle remains in traffic and intends to follow its current path, it will send out mobile agents and refresh the information. When the vehicle diverts from its path and chooses a new intention, it does not need to inform all the infrastructure agents on the abandoned path to cancel the visit.

When looking for a route the vehicle agent uses an exploration strategy inspired by Ant Colony Optimization [4]. The vehicle agent dispatches mobile agents similar to the ones used in the intention propagation. These mobile exploration agents are dispatched across possible route alternatives. The alternatives are calculated using the ACO based algorithm described in [4]. Contrary to the mobile intention agents, these exploration agents do not store information on the infrastructure agents. They merely keep track of the estimated arrival times. Upon reaching the destination, the mobile exploration agent informs the vehicle agent of the estimated arrival time for this route alternative.

Infrastructure agents receive information about pending visits in the form of intentions. For every future moment in time, they have a number of vehicles that has committed to pass by. This information, combined with observations of the historic travel times on the road, is used by a neural network to forecast the traversal time at that future moment [5]. It is this information that is shared with the mobile agents.

3 Related Work

In this section we describe related work on several ATIS systems. We focus first on anticipatory ATIS systems: ATIS systems predicting future traffic states in order to guide traffic (Section 3.1). Next we focus on studies looking at multiple user classes in the evaluation of the ATIS (Section 3.2).

3.1 Anticipatory ATIS Systems

ATIS systems taking into account traffic predictions have the potential to not only allow participating drivers to reach their destinations faster, they also have the potential to reduce traffic congestion. By diverting traffic before congestion occurs, the congestion buildup can be avoided.

Wahle and Schreckenberg present a multi-agent based framework combining simulation and real-world traffic data to make short term traffic predictions [6]. They also discuss the need for anticipatory route guidance and the need to model drivers responses to the information they receive but leave the latter as future work.

Kai and Mo also present a real-time traffic information simulation and prediction system [7]. Instead of using neural networks to learn the traffic networks response to traffic, Kai and Mo employ an approach based on support vector machines, namely *Accurate on-line support vector regression* or AOSVR.

Both Wahle and Schreckenberg and Kai and Mo use a combination of historical information, real-time information and simulation to provide the additional information their ATIS's present to the driver. In AVRIP these components are also present, but more implicitly. The neural network training process combines historical information with real-time traffic information to train the networks. When the mobile agents described in Section 2 explore the traffic network they keep track of a time horizon. The route found by the mobile agent combined with time horizon indicating the estimated time of arrival is the equivalent of simulating the route using the information stored in the artificial neural network. The benefit of AVRIP and its use of mobile agents is that information is stored and reasoned on in a decentralized, scalable way.

3.2 Multiple User Classes

Many ATIS systems are presented and evaluated in literature. Authors rarely analyze the impact of partial participation rates on the systems evaluation. Some research on how the information presented by an ATIS system is received by the community of drivers, often dividing the community in multiple classes can be found in literature.

Adler, for example, looks at more fine grained classes for drivers and provides test subjects with different types of information on a hypothetical network to see how they behavior of the test subjects changes due to the information [8]. The classes Adler looks at are (1) basic map information, (2) route guidance, (3) traffic advisory information and finally (4) a combination of route guidance and traffic advisory information. The study presented in this paper is limited to classes (2) and (4), as even the drivers not participating in the ATIS are assumed to have access to basic route guidance.

Peeta and Mahmassani also take into account multiple user classes when evaluating their rolling horizon solution framework [9]. In their paper they argue that (1) online route guidance systems are a necessity because of the dynamic nature of traffic and (2) one should not assume all users have the same access or response to the information provided by an ATIS. These two claims are in line with the position of this paper.

In their paper, Wunderlich et al. present a study similar to the one described in this paper [2]. While the ATIS system described by Wunderlich et al. differs greatly from the one presented in Section 2, the focus of the study was similar: How do multiple user classes influence the impact of the additional information.

The study of Wunderlich et al. is of particular interest because it does not only focus on the overall impact of different user classes (participating and non-participating), but also on the impact of the relative size of the classes on other classes.

The main difference between the ATIS system described in [2] is the systems architecture. Where the architecture described in this paper is fully decentralized, the architecture used by Kauffman is centralized. Many of the research questions are similar though. Much attention is given to the impact of the participation rate on the performance of the guidance system. The evaluation of the centralized guidance system is also based on simulations.

The experiments conducted by Wunderlich et al. show that as the participation rate increases, the benefit for the participating drivers drops. As more and more drivers will be taking the detour, the travel time on the detour will rise and the original congestion will resolve more quickly. A second observation is that for non-participating drivers the effect is the opposite: As the participation rate increases, the non participating vehicles will benefit. These are the observations we set out to verify in our decentralized guidance system.

4 Experiment Setup

In this section we will describe the experiment setup. All experiments are simulation based. The simulation used is described in [10] and uses a spatial model to position vehicles on the road. The vehicles behavior is based on the intelligent driver model [11] combined with the MOBIL [12] lane changing model.

In the simulated scenario two classes of drivers are considered. Drivers participating in the AVRIP guidance system and drivers not participating in the system. Drivers not participating in the system will use an A* based path finding algorithm to calculate their route. Drivers participating in the AVRIP guidance system will use the information obtained from the mobile exploration agents to choose a route and will propagate this using the mobile intention agents. The proportion of drivers participating is what we refer to as the participation rate.

Every simulation uses the same origin destination (OD) matrix. This OD matrix is fully disaggregated, it contains the start time, start location and destination for every vehicle participating in the system. Depending on the participation rate, the vehicles described in the OD matrix are divided between the two classes based on a random number generator.

The AVRIP route guidance system depends on many parameters. During these experiments these parameters were fixed to the ones found in Table 1. These parameters are not guaranteed to be the optimal ones, but previous experiments have shown that they are a good choice [4,5].

The overall experiments setup is as follows: We have constructed one OD matrix. For every participation rate we simulate this OD matrix 20 times, each time with a different random seed. Changing the random seed also affects how the OD matrix is divided between participating and non-participating vehicles.

Coordination mechanisms such as AVRIP are no silver bullets. They can help traffic networks cope with more traffic, increasing their capacity under congestion, but they can only do so for a limited traffic increase. The impact of the coordination system is only noticeable when traffic levels are in this interval. Building an OD matrix for a realistic traffic network in a realistic simulation where traffic levels on all roads are in this interval is nearly impossible. Because of this limitation, we only use a small artificial traffic network. The limited size of the network allows us to thoroughly analyze the simulation outcome.

Figure 1 shows the road network used in the scenarios. The network is constructed as follows: A main traffic axis $A \rightarrow F \rightarrow E \rightarrow B$ is the shortest and - in freeflow traffic - the fastest route between A and B. The route $A \rightarrow F \rightarrow G \rightarrow B$ at the bottom offers an alternative route between A and B, but is slightly slower than the first route. The traffic between A and B is generated so that node E receives a traffic flow just below its capacity. At the top of the network, there is route $C \rightarrow E \rightarrow D$. When traffic flows across that route, it causes congestion in E for both the $C \rightarrow E$ and the $F \rightarrow E$ edges. The only way of avoiding the congestion for the $A \rightarrow B$ traffic is to use the detour through G.

5 Experiment Analysis

In this section we will analyze the outcome of the experiments. We start by discussing how the vehicles performance is measured. The next step is to analyze the results graphically. Finally we analyze the experienced travel times for all vehicles and look for a statistically significant reduction in travel time using the t-test.

5.1 Travel Time Evaluation

Not all vehicles in the simulation have the same origin destination pair which makes comparison of individual vehicle performance difficult. In order to allow such comparison we introduce a scoring mechanism. In [2], the authors use the average travel times of both participating and non-participating vehicles and compare these averages. We believe using the average travel time has two serious drawbacks: (1) Longer routes will have a greater impact on the end result and (2) by aggregating the performances we loose the information of individual vehicle performances. The second drawback prevents us from looking at the distribution of the results and denies us the possibility to compare the performance of the same vehicle across different simulations.

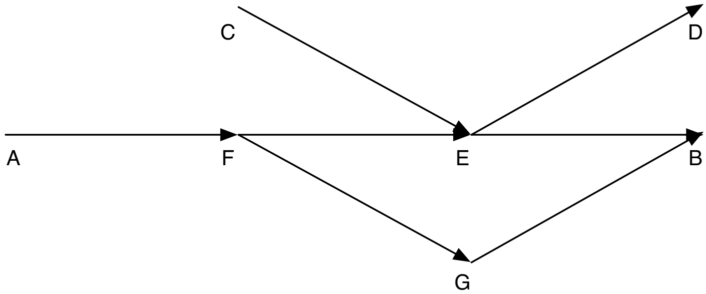


Fig. 1. The road network used in the scenarios. $A \to F \to E \to B$ is the main traffic axis. $A \to F \to G \to B$ is the detour route and $C \to E \to D$ is the congestion causing axis.

Taking these problems into account we score the performance of a vehicle v_i by dividing the vehicles travel time $(t(v_i))$ by the travel time of that same vehicle in a totally unguided traffic situation $t_{p_0}(v_i)$. This last value, $t_{p_0(v_i)}$, is the vehicles travel time in the simulation with a participation rate of zero (p_0), meaning all vehicles use the A* based guidance. We will refer to the quotient of these values as the *Q-score*.

$$Q - score\,(v_i) = \frac{t(v_i)}{t_{p_0}(v_i)} \tag{1}$$

If a vehicle has the same travel time as it does in the p_0 unguided experiment, that vehicles Q-score will be 1. When the vehicle performs better than in the base experiment the Q-score will be lower than 1, when it performs worse the score will be higher than 1.

5.2 Graphical Analysis of Simulation Results

Figure 2 shows the Q-score for participating and non-participating vehicles in all of the experiments. The error bars denote the 95% confidence interval surrounding the average. A first observation that can be made is that the Q-scores of the participating vehicles are lower than those of the non-participating vehicles. As the participation rate increases, both populations start to benefit equally. A trend that is confirmed in Section 5.3. This observation is a validation of the observations made by Wunderlich et al. in [2].

Figure 3a and 3b show the distribution of Q-scores for participating and non-participating vehicles for one simulation in the 10% and 90% participation rate experiments. The histogram combined with the full density line shows the distribution of Q-scores in the experiment while the dashed distribution line allows comparison with the p_0 unguided base case.

As the distributions show the guidance system results in a shift towards the lower Q-scores for most of the vehicles. Here, again, the results indicate that the

Table 1. The parameter values for this set of experiments

Parameter	Value
average injection interval	0,1 ticks (1 s = 1000 ticks)
participation rate	0,1
duration	30 min
reconsideration threshold	0,1
reconsideration rate	10
alpha (ACO)	20
beta (ACO)	30
gamma (ACO)	0,3
rho (ACO)	0,8
phi (ACO)	20
tau_0 (ACO)	50
tau_max (ACO)	1000
max nbr of hops	250
nbr of explorers	10

benefit is greater for the participating vehicles, but that significant number of non-participating vehicles also benefits from the coordination.

To estimate the impact of AVRIP under certain participation rates on the experienced travel times and the resulting congestion in the network we plot the ratio between the actual duration and the static duration vehicles experience on link $F \rightarrow E$ against the vehicles arrival time on that road. Figure 4 shows that experienced travel time rises steeply for a participation rate of 10% (Figure 4a on the left). The increase in travel time is less in the case of a participation rate of 50% (Figure 4b in the middle) and is greatly reduced in the case of 90% (Figure 4c on the right).

Based on Figure 4 it appears the information provided by the AVRIP system is able to persuade drivers to choose the alternative road thus avoiding congestion buildup.

5.3 Statistical Analysis of Simulation Results

To verify the impact of using AVRIP we apply a paired t-test to each simulation outcome individually. The hypothesis in this test is that the travel times, not the Q-score, of the vehicles in the experiment are equal to or higher than in the p_0 unguided case. A one-sided paired t-test is then used to reject this null hypothesis

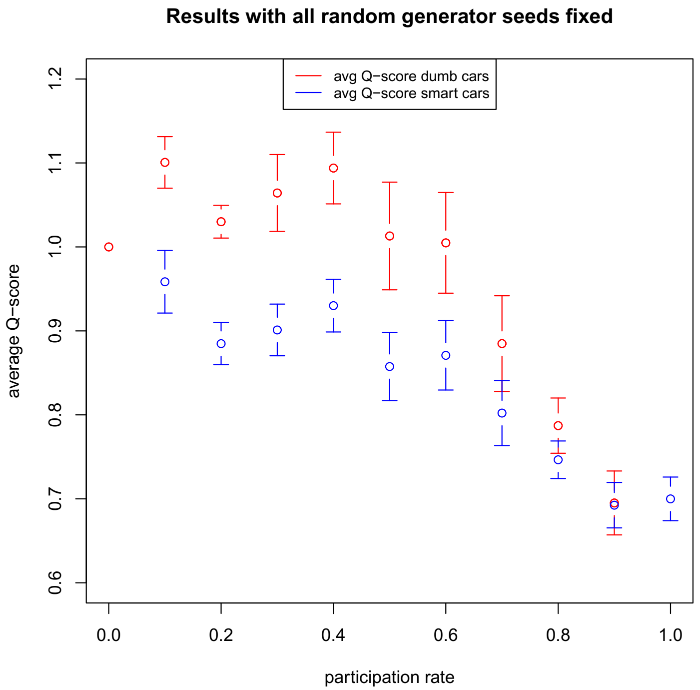
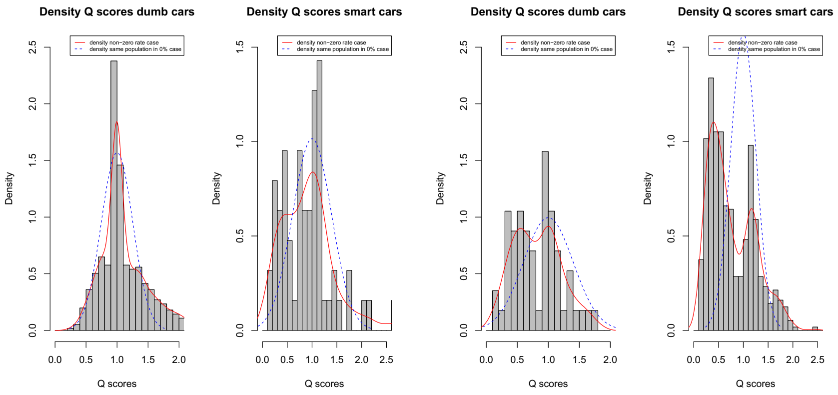


Fig. 2. Q-scores for all simulations with varying participation rates

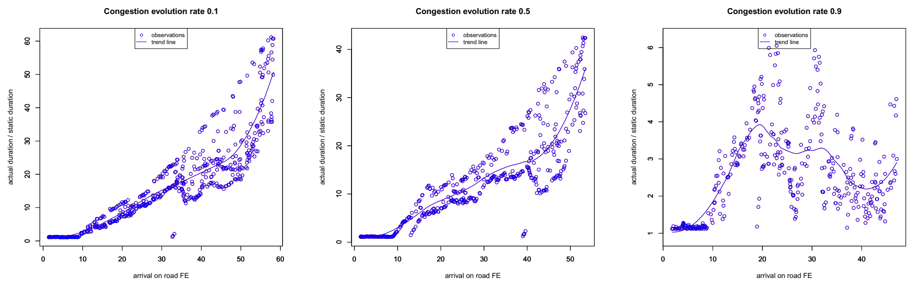
and conclude that the travel times in the experiment are lower than in the p_0 unguided case. We repeat this process for only the non-participating population, only the participating population and finally the total population. The summary of these tests are in Table 2. The maximum, minimum and average p-values for all experiments are listed along with the number of simulations where the p-value was below 0.05.

As Table 2 shows, the participating vehicles are experiencing lower travel times in nearly all simulations. For the experiment with participation rate $p = 0.1$, only 14 of the simulations result in a statistically significant decrease of travel times. But for simulations with a participation rate of 20% or higher almost all experiments result in successful t-tests. In experiments with high participations rate the non-participating vehicles also benefit and experience reduced travel times. Looking at the last column, we see that for experiments with a participation rate between 20% and 70% the majority of simulations result in statistically relevant reduction in experienced travel times for the entire population. For participation rates above 70%, all simulations result in reduced experienced travel times for the entire population.



(a) Participation rate 10% (b) Participation rate 90%

Fig. 3. With a participation rate of 90% (right) the dumb vehicles experience less congestion, resulting in lower Q-scores compared to the 10% rate (left)



(a) Participation rate 10% (b) Participation rate 50% (c) Participation rate 90%

Fig. 4. Evolution of the congestion rate for participation rates 10%, 50% and 90%

The failure of many of the experiments with participation rates below 20% indicates that this is the critical participation rate needed for the coordination system to successfully assist the drivers with accurate predictions. In participation rates below this boundary, the guidance system fails to forecast the congestion and divert traffic.

Table 2. Summary of the t-test results for all simulations

	non-participating				participating				total population			
p-rate	average	min	max	< 0.05	average	min	max	< 0.05	average	min	max	< 0.05
0.1	6.5E-01	1.8E-03	1.0E+00	4	6.7E-02	4.8E-05	3.4E-01	14	5.1E-01	2.1E-05	1.0E+00	6
0.2	2.2E-01	1.4E-05	9.5E-01	11	4.3E-03	2.5E-11	7.7E-03	**20**	3.0E-02	1.4E-12	2.9E-01	18
0.3	3.5E-01	2.7E-08	1.0E+00	8	5.9E-03	8.3E-14	1.1E-01	19	1.3E-01	3.0E-19	1.0E+00	15
0.4	6.5E-01	4.0E-15	1.0E+00	4	3.1E-04	2.7E-19	2.8E-03	**20**	1.2E-01	3.4E-32	7.5E-01	15
0.5	3.6E-01	2.4E-30	1.0E+00	10	1.7E-05	1.5E-32	2.4E-04	**20**	4.3E-02	2.4E-60	5.9E-01	18
0.6	2.4E-01	1.2E-26	1.0E+00	11	1.2E-02	1.0E-37	2.4E-01	19	5.1E-02	3.6E-61	1.0E+00	19
0.7	7.6E-02	1.6E-25	8.5E-01	18	2.1E-11	6.9E-56	2.5E-10	**20**	1.2E-08	5.5E-78	2.2E-07	**20**
0.8	9.1E-05	3.6E-16	1.8E-03	**20**	2.1E-25	1.0E-59	4.3E-24	**20**	4.9E-27	1.0E-72	9.8E-26	**20**
0.9	1.8E-05	5.3E-10	1.7E-04	**20**	2.3E-39	8.2E-81	3.8E-38	**20**	3.5E-42	4.2E-89	6.0E-41	**20**
1.0	NA	NA	NA	NA	2.3E-43	2.2E-86	3.4E-42	20	2.3E-43	2.2E-86	3.4E-42	20

6 Concluding Remarks

In this paper we analyzed the impact of varying participation rates on the efficiency of Anticipatory Vehicle Routing using Intention Propagation. By simulating a small road network under various circumstances, we were able to thoroughly evaluate the travel times for both participating and non-participating vehicles.

As shown in Section 5, the coordination strategy only works if at least 20% of vehicles participate in the guidance mechanism. If less than 20% of the vehicles participate, the participating population not always benefits from the forecast information.

However, if more than 20% of the population participates, the coordination mechanism yields significant decreases in travel times for both participating and non-participating vehicles. The results show that as the participation rate increases, the benefit for the non-participating vehicles is significant. For the participating vehicles the benefits are significant, but stagnate with higher participation rates, something also observed by Wunderlich et al. in [2].

Future work will focus on more large scale and realistic scenarios. The thorough analysis of the artificial network in this paper shows the potential of AVRIP and the influence of the participation rate. Further research confirming these findings in realistic large scale networks is the next step.

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